International Journal of Electronics,
Communication & Instrumentation Engineering
Research and Development (IJECIERD)
ISSN(P): 2249-684X; ISSN(E): 2249-7951
Vol. 5, Issue 5, Oct 2015, 35-42

HUMAN SKIN DETECTION USING FUSION TECHNOLOGY

PRATIBHA B. KHADSE & SHAILAJA GAIKWAD

Department of Electronics, Terna College of Engineering, Maharashtra, India

ABSTRACT

Skin detection is a process of finding skin colored pixels and regions in an image or a video. An effective skin detection process is the one which differentiates skin region under any illumination conditions and works well with persons of any ethnicity. Different skin detection methods however have been successfully applied but they are prone to false skin detection and also not able to cope up with the variety of human skin colors. Additionally requires high computational costs. In this paper a dynamic threshold approach is implemented which reduces computational costs as no training is required, and it further improves the accuracy of skin detection. Additional feature is implemented i.e. fusion of a histogram model and Gaussian model for automatic human skin detection in color image(s) that gives good results when either of this method is employed individually.

KEYWORDS: Color Space, Dynamic Threshold, Fusion Strategy, Gaussian Model, Skin Detection

INTRODUCTION

With the progress of information society today, images have become more and more important. Among them, skin detection plays an important role in a wide range of image processing applications as skin is the most widely used primitive in human image processing. Applications such as detecting and tracking of human body parts [1], face detection [2], naked people detection, people retrieval in multimedia databases [3] and blocking objectionable content [4], all benefit from skin detection as detection of skin serves the primary step.Skin detection is not as easy task as the skin appearance in images is affected by various factors such as illumination, complex backgrounds, camera characteristics and ethnicity. Thus an effective skin detection is the process of identifying human skin colors of different ethnic and under different illumination conditions.The approaches to classify skin in images can be grouped into three types: parametric, non-parametric and explicit skin cluster definition methods. The parametric models use a Gaussian color distribution whereas non-parametric methods estimate the skin-color from the histogram obtained from training data. Skin clustering explicitly defines the boundaries of skin in a given color space, generally termed static skin filters. The main drawback of skin clustering is a high number of false detections.

In general skin detection process has two phases

- Training Phase
- Detection Phase

Training a Skin Detector Involves Three Basic Steps

- Collecting a database of skin patches from different images. Such a database typically contains skin colored patches from variety of people under different illumination conditions.

- Choosing a suitable color space. Since skin color occupies a part of such a space, which might be a compact or a large region in the space
- Learning the parameters of a skin classifier

Detection Phase Involves

- Converting the image (under skin detection) into the same colour space that was used in the training phase.
- Classifying each pixel using skin classifier to skin or non skin
- Post processing using morphology to impose homogeneity on the detected regions

One of the simplest and common method in detecting human skin is to define a fixed decision boundary (threshold) i.e. the training phase .The pixel values that lies between these boundaries are selected as skin pixels else as non-skin pixels. All this approaches are based on skin classification based on color information. As for any given color space, skin color occupies a part of such a space, which might be a compact or large region in the space. Other approaches are multilayer perceptron [5]–[7], Bayesian classifiers [8]–[10], and random forest [11]. These approaches uses single features, and are successfully applied to human skin detection but still suffer from high false detection that is low accuracy and also requires large training stage for finding threshold value(s) for detecting human skin.

In this paper, we propose a fusion approach that is fusion of two features that is the histogram model and Gaussian model to perform automatic skin detection. Firstly, we employ an online dynamic approach as in [12] to calculate the skin threshold value(s) thereby eliminating any training stage beforehand. Secondly, a histogram model and a Gaussian model are used to model the skin and non-skin distributions. And finally, a fusion of these two features is used to perform automatic skin detection.

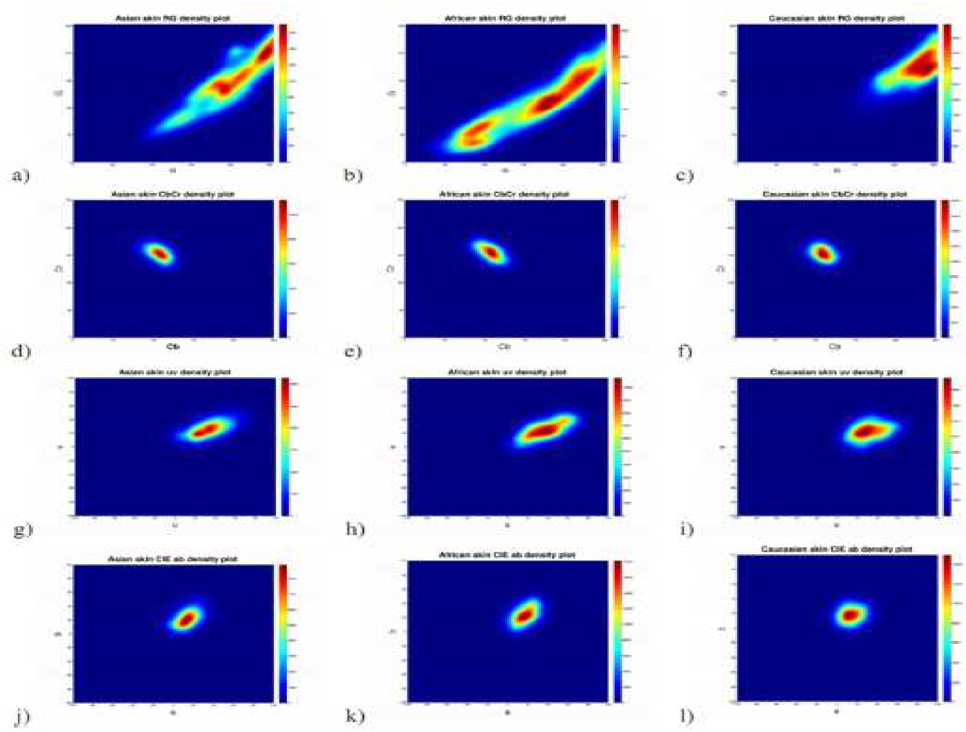


Figure 1: Density Plots of Asian, African and Caucasian Skin in Different Color Spaces. Each Row Represents Different Color Space and Columns from Left to Right Represent Asian, African and Caucasian Respectively

RELATED WORK

Human skin detection is considered as a two-class classification problem, and has become topic of attention from researchers in recent years [40.1, 2],specifically those dealing with biometrics and computer vision aspects.

For example, Sobottka and Pitas[13] used the HS color space with fixed skin threshold in the range of of R_H=[0,50] and R_s=[0.23, 0.68].Wang and Yuan [14] used RG space and HSV space where the skin threshold values are set to be within the range R_r=[0.36, 0.465], R_g= [0.28, 0.363], R_h=[0,50], R_S=[0.20, 0.68] and R_V=[0.35, 1.0] to differentiate skin and non-skin pixels. Dai and Nakano [15] used a fixed range on I component in YIQ space for detecting skin pixels from images containing mostly people with yellow skin. All the pixel values in the range, RI = [0; 50] are considered as skin pixels in this approach. Chai and Ngan [16] proposed a face segmentation algorithm in the CbCr plane with skin color ranges were RCb = [77; 127], and RCr = [133; 173] defined as skin pixels.However all these approaches resulted in high false detections when there were people from different ethinicity ,with complex backgrounds and different illumination conditions. The skin color of people belonging to Asian, African, and Caucasian groups is different from one another as in Figure 1. Hence some robustness has be achieved via the use of a suitable color space. Also the threshold values varied from one color space to other. Thus to handle all the drawbacks of the fixed threshold methods felt a need to have a technique which can dynamically learn the skin tone of people and so dynamic threshold classification technique is used.

METHODS

Figure 2 Shows the Block Diagram of the Method used for Skin Detection

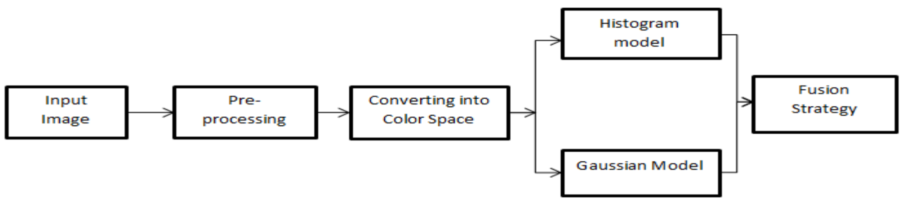


Figure 2: Block Diagram of the Proposed System

Pre-Processing

Initially from the selected image only face region is cropped to dynamically learn the skin pixels of the face region. Here the assumption used is that the face and body of a person always share the same colors. The face region now includes smooth (i.e., skin) and non-smooth regions (i.e., eyes, eye brown, mouth, etc.). Since the interest lies only in the smooth regions , non smooth regions were removed using canny edge detector. The detected edge pixels are further dilated using a dilation operation to get the optimal non-smooth regions. The calculated non-smooth region is then subtracted from the face region and smooth region is obtained and thus getting the smooth regions in the cropped face.

Color Space

Image representation can be done in a number of different color spaces. But selecting the right color space is of utmost importance. Here we proposed the use of LO color space as it has been proved that human visual system uses

opponent color encoding. The image obtained after the preprocessing stage is then transformed to LO color space. The conversion formula given in Equations 1,2 and 3.

$I = L(G)$

$R_g = L(R) – L(G)$

$B_y = L(B) – (L(R) + L(G)) /2$

Where $L(x)=105+\log_{10}(x+1)$

Histogram Model

An image Histogram acts as a graphical representation of the lightness/color distribution in a digital image. It plots the number of pixels for each value. Image histograms can be useful tools for thresholding

The lower and upper boundaries are now learned using histogram model for both the color channels, I and By. Based on these calculated dynamic threshold values each and every pixel in the color image is classified as skin and non-skin.

Gaussian Model

The Gaussian model is a sophisticated model that is capable of describing complex- shaped distributions and is popular for modeling skin-color distributions.

The threshold skin-color distribution in the histogram would be modeled through normal probability distribution functions defined as

$$y = f(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \; e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

Where μ is mean of the function and σ is the standard deviation.

The mean and standard deviation for each color channel i.e. I and By is calculated. Finally they are then compared to the values of the main image to get the final detected skin regions.

Fusion Strategy

Lastly in order to increase the robustness of the skin detection algorithm, a fusion strategy is proposed by combining the two incoming single features into a single representation. This can be done by applying and rule to both models.

RESULTS AND ANALYSIS

The proposed method was evaluated and compared with the other state-of-art methods. Evaluation was done using The Pratheepan’s dataset [12] consisting of a set of images downloaded randomly from Google. These random images are captured with a range of different cameras using different color enhancements and under different illuminations. Some images are a taken from the ETHZ pascal dataset while some are from Stottinger dataset [17].Others were taken randomly from the internet

The proposed approach combines two individual methods that is Histogram Method and the Gaussian method. Comparison of individual methods with the fusion scheme is shown in Figure 3, where black indicating non-skin region while white as skin region.

Table 1: Comparison between our Proposed Method and Used Individual Methods

Classifier	Accuracy	Precision	F-score	True Positive Rate	False Positive Rate
Fusion	0.8975	0.8790	0.8263	0.7796	0.1210
Histogram	0.8072	0.6268	0.7626	0.9735	0.3732
GMM	0.8902	0.8145	0.8075	0.8006	0.1855

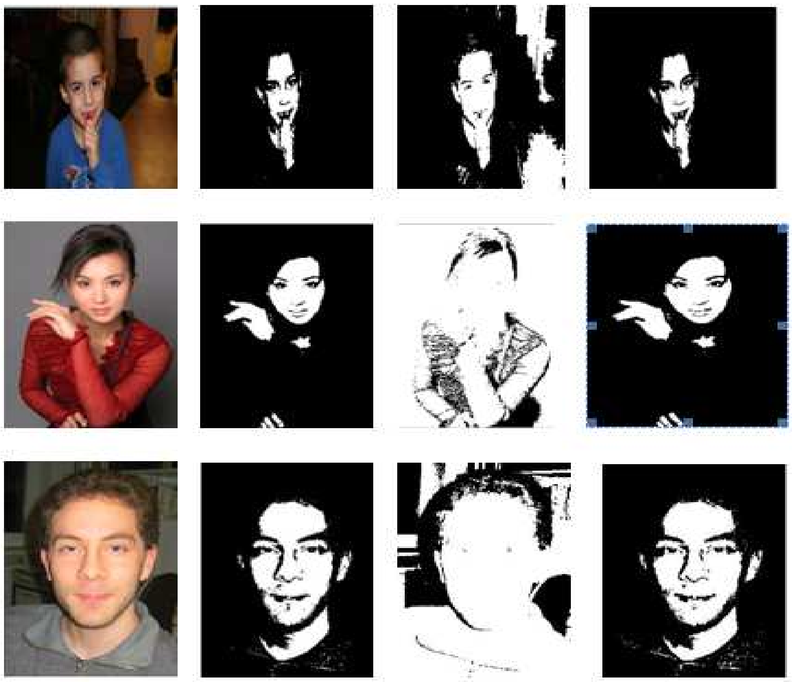


Figure 3: Column from Left to Right Represents Original Images, Gaussian Model's Result, Histogram Result and Fusion Approach's Result

From the table 1 it can be observed that fusion scheme resulted in highest accuracy, precision and F-score then the individual feature vector. Figure 3 visualises the output of the different methods. It can be seen that histogram model not able to detect most of the skin regions as compared to the Gaussian model.

Apart from comparing with the individual methods that are involved, the comparison of the proposed method is also carried out with the other state-of-art methods . Figure 4 shows the visual comparison while table 2 shows the associated improved values.

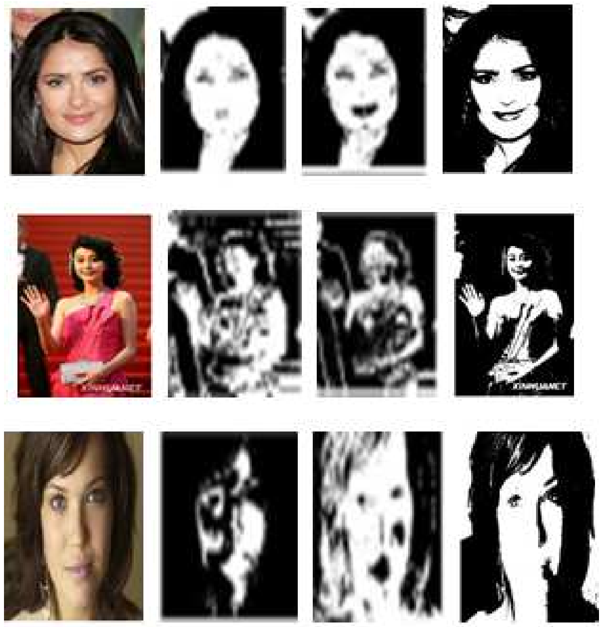
Figure 4 shows comparison of Random Forest [11] with our approach. For random forest [11], 1990 image frames are randomly chosen for training and remaining images are used for testing. From those 1990 images, around 3 million pixels were randomly chosen and 15 trees were trained. Each tree extracts 70% of the pixels, respectively, for training , which consumed time in minutes. From Figure 4 many images performed well with the proposed method as opposed to Random Forest. Moreover Random Forest is time consuming as number of trees increases to increase the accuracy of the

method. Quantitatively from the table 2, which compares the fusion method with other state-of-art methods, proves that the proposed method has improved accuracy , precision and recall.

Table 2: Comparison between Different Classifier Performance

Classifier	Accuracy	Precision	Recall
Proposed Method	0.892	0.971	0.633
Random Forest [11]	0.877	0.738	0.740
Static Threshold [18]	0.833	0.474	0.557

Figure 4: Comparison between Random Forest [11] and Proposed Method. (a) Original Image (b) Random Forest Result and (c) Proposed Method Result



(a) (b) (c) (d)

Figure 5: (a) Original Image (b) Method[18] (c) Method [12] and (d) Proposed Method

Figure 5 shows the comparison between two methods [12] and [18] with our method. It is observed that our method performed well in terms of illumination, background image, diferent camera characteristic, and different ethnicity

For example in image 2 (read from top to bottom) the method [12] and [18] are not able to detect even the face region .While there is noise in mostly the skin detected images. One advantage of our method is it doesn't require training stage hence reducing the computational cost when compared to [12] and [18].

CONCLUSIONS

Thus a fusion technique based on histogram model and Gaussian model has been proposed for automatic human skin detection in images. The method when evaluated proved to be better then the other state-of-art methods and it reflected its better performance in terms of accuracy and other parameters. However the proposed method does fails for false eye detection and optimal cropping of the face. As when a false face region is obtained, resulting in wrong learning of the skin pixels and false dynamic thresholds will be generated and thereby resulting in false detection of skin regions.

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